Misallocation and productivity in New Zealand

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Abstract

New Zealand's total factor productivity growth slowed considerably in the 2000s. One factor that may be driving this lower productivity growth is poor resource allocation among firms within the same industry. To investigate this possibility, this paper applies the Hsieh and Klenow (2009) method to data from Statistics New Zealand's Longitudinal Business Database for 2001 to 2012. It finds that the impact of resource misallocation on productivity increased over this period. If capital and labour were allocated optimally across firms within each industry, total factor productivity would have been 56 percent higher in 2001, with this figure steadily rising to 77 percent in 2012. This increase in within-industry misallocation is apparent in the primary, goods-producing and services sectors, as well as in the majority of industries that make up these sectors. In addition, initial results suggest that within-industry misallocation has been a much greater drag on total factor productivity growth than between-industry resource allocation, with between-industry allocation actually making a small, positive contribution to productivity growth over the 2001 to 2012 period. Another implication of the HK model is that many small firms in New Zealand are larger than their optimal size given their low productivity levels. The general explanation for this result internationally is that small firms are subsidised through size-contingent policies and/or less stringent enforcement of regulations. Given its policy settings, this argument is harder to make for New Zealand. However, the result is consistent with previous research showing a comparatively poor "up-or-out" dynamic among New Zealand firms.

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1 Introduction

In comparison with other developed countries, New Zealand's productivity performance has been poor. New Zealand is the only OECD country with a below-average level of economy-wide labour productivity in 1980 to also experience below-average labour productivity growth between 1980 and 2010 (Conway & Meehan, 2013).

Moreover, like many other countries, New Zealand's total factor productivity (TFP) growth has slowed over the 2000s, with the slowdown beginning prior to the Great Recession (Figure 1).[1] Although average annual output growth in New Zealand from 2000 to 2008 was somewhat higher than output growth in the 1990s, this growth was due to greater input growth more than compensating for slower productivity growth. Average annual TFP growth from 2000 to 2008 was only 0.6 percent, compared with 1.9 percent between 1990 and 1997, and 1.8 percent between 1997 and 2000. In the aftermath of the Great Recession, both output growth and TFP growth slowed considerably, with average annual TFP growth of just 0.2 percent from 2008 to 2015. This slowdown in TFP growth is concerning given that TFP is a crucial force in defining income differences across countries. For instance, Hsieh and Klenow (2010) estimate that between 50 and 70 percent of cross-country income differences are generated by differences in TFP levels, and that TFP also exerts a powerful indirect effect on physical and human capital accumulation.

This paper investigates whether changes in within-industry resource misallocation may have contributed to New Zealand's poor productivity performance in the 2000s.[2] This paper is the first part of a strand of research which examines three questions: How important is a deterioration in allocative efficiency in accounting for New Zealand's TFP performance over the 2000s, and does this vary across sectors? What are the key distortions that have contributed to changes in allocative efficiency? What changes, particularly policy changes, might have been important in explaining the deterioration in allocative efficiency? This paper applies the method of Hsieh and Klenow (2009) (henceforth, 'HK') to New Zealand firm-level data from 2001 to 2012 to examine the role of within-industry misallocation in New Zealand. In particular, it aims to address the first question and to provide initial results for the second question. Fuller analysis of the second question, along with the third question are left for future work.[3]

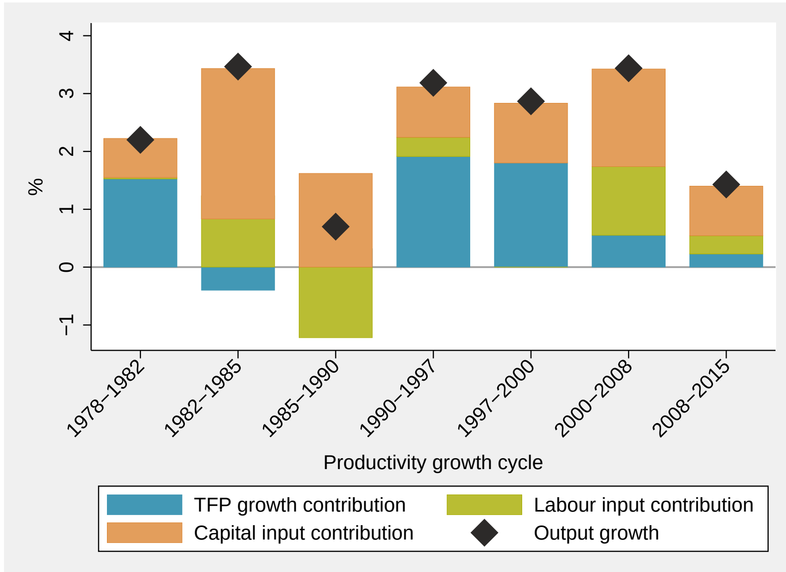
Previous work suggests that within-industry resource allocation may be important in explaining New Zealand's slow productivity growth in the 2000s. First, within-industry growth appears to be important and the slowdown in New Zealand's TFP growth in the 2000s reflects a slowdown in growth within almost all industries (Conway & Meehan, 2013). Also, while there was a shift of employment to lower-labour-

[1]Statistics New Zealand productivity data are available for the "former measured sector" (which includes ANZSIC06 industries AA-LL1) from 1978 onwards, and for the "measured sector" (which includes ANZSIC06 industries AA-LL1, MN and RS) from 1996 onwards (see Statistics New Zealand 2014 for details). The Statistics New Zealand series presented here are spliced series for the former measured sector up to 1995, and the measured sector from 1996. However, the general trends are similar if the former measured sector is used for the entire period.

[2]See Conway (2016) for a broader discussion of New Zealand's productivity underperformance, the economic reasons behind this underperformance, and policy directions for improvements.

[3]This paper is part of ongoing Productivity Hub work under the research theme 'Resource allocation' (for details, see Nolan 2014).

Figure 1: Contributions to output growth over productivity growth cycles[ab]



Source: Statistics New Zealand March 2016 Productivity release

[a]See The latest full productivity cycle is 2000 to 2008. The most recent period of 2008 to 2015 is an incomplete productivity cycle. Breaking the series into growth cycles allows for average growth rate comparisons that account for variation in capacity utilisation over cycles. Statistics New Zealand calculates these cycles on a 'peak-to-peak' basis using a Hodrick-Prescott filter. See Statistics New Zealand (2007) for more details.

[b]See Footnote 1 for details of industry coverage.

productivity industries in the 1990s, this was not the case in the 2000s, with employment shifts across industries making a small but positive contribution to labour productivity growth (Meehan, 2014) and resource shifts making a positive contribution to TFP growth (Maré, Hyslop & Fabling, 2015).

Moreover, New Zealand is not unique in its experience of a slowdown in productivity growth in the 2000s and poor growth in the aftermath of the Great Recession. Overseas literature suggests that at least part of the explanation for these trends is that misallocation across firms has increased. For example, Barnett, Broadbent, Chiu, Franklin and Miller (2014) suggests that an increase in misallocation has made an important contribution to the UK's productivity slowdown. OECD (2015) also notes that net lending in the UK decreased in the aftermath of the Great Recession. Banks were increasingly reluctant to write-down non-performing loans made to unprofitable firms while lending to young but productive firms (that were less likely to have a credit history or collateral) decreased. For southern European economies, Gopinath, Kalemli-Ozcan, Karabarbounis and Villegas-Sanchez (2015) suggests that the decline in the real interest rate, often attributed to the euro convergence process, led to a decline in TFP as increased capital flows were misallocated towards firms that had higher net worth but that were not necessarily more productive. This work is also part of a wider literature that suggests economic dynamism has decreased, such as Decker, Haltiwanger, Jarmin and Miranda (2014), which finds a secular decline in dynamism in the US.

For New Zealand, this paper finds that the potential TFP gains from more efficient resource allocation are large and increasing over the 2000s.[4,5] If capital and labour were allocated optimally across firms within each industry, New Zealand's aggregate TFP could have been 56 percent higher in 2001, with this figure rising steadily to 77 percent in 2012. This increase in misallocation is evident in the primary, goods-producing and services sectors, although the level of misallocation varies across these sectors. The potential TFP gains from more efficient resource allocation is highest in the primary sector, which also experienced a large increase in misallocation over time (from 89 percent in 2001 to 153 percent in 2012). There are also large potential TFP gains from better resource allocation in the services sector, but this sector has the smallest increase in misallocation over time (from 72 percent in 2001 to 77 percent in 2012). The gains for the goods-producing sector are lower, and went from 36 percent in 2001 to 67 percent in 2012. Potential TFP gains in the manufacturing subset of the goods-producing sector were even lower, but more than doubled over time (from 21 percent in 2001 to 48 percent in 2012).

Although these gains seem large, they are broadly in line with existing literature that applies the HK method to other developed countries. For example, Hsieh and Klenow (2009)'s original paper found that potential within-industry allocative efficiency gains in US manufacturing were about 36 percent in 1998, growing to about 43 percent in 2005. In addition, while most of the existing literature focuses on manufacturing industries only, two existing studies that apply the HK method to other sectors find that misallocation is higher in non-manufacturing industries (Dias, Marques & Richmond, 2015; García-Santana, Moral-Benito, Pijoan-Mas & Ramos, 2016), which is consistent with the finding for New Zealand.

A counterfactual exercise also indicates that within-industry misallocation has been a much larger drag on TFP growth than between-industry allocation, with between-industry allocation actually making a small, positive contribution to productivity growth over the 2001 to 2012 period. In addition, initial results suggest that output distortions are more important than capital distortions, but that output distortions have been relatively stable over time while capital distortions have been increasing. These results suggest that increasing capital distortions are an important factor behind New Zealand's deteriorating allocative efficiency.

Another implication of the HK model is that many small New Zealand firms are larger than their optimal size given their relatively low levels of productivity. The general explanation for this result internationally is that small firms are subsidised through size-contingent policies and/or less stringent enforcement of regulations. However, this argument seems less applicable to New Zealand given its policy

[4]While it would have been preferable to examine misallocation and productivity over a longer time period, and in particular, to compare the 1990s with the 2000s, at the time of writing, appropriate firm-level data were only available from 2001 to 2012.

[5]Throughout this paper, I use the Statistics New Zealand convention of referring to a broad grouping of industries as a sector. In this paper, industries are generally ANZSIC06 3- or 4-digit industries (see Section 2 for more details on the level of industry disaggregation). The primary sector consists of agricultural, forestry, fishing and mining industries; the goods-producing sector consists of manufacturing, utilities and construction industries; and the services sector consists of market-service industries such as professional and administrative services, finance, retail and wholesale. Many existing papers in this area focus on the manufacturing part of the goods-producing sector, therefore, I also present separate results for the manufacturing sub-sector throughout.

settings. Instead, I argue that this finding is consistent with previous research that highlights the lack of “up-or-out” dynamics among New Zealand firms (such as Criscuolo, Gal and Menon 2014.). I also speculate that low-productivity New Zealand firms are able to grow larger than their optimal size due to the limited extent of the market and a lack of competition

This paper discusses preliminary findings from the application of the HK method to New Zealand firm-level data, and there are various potential extensions and applications of this basic method. For example, some of the model’s assumptions could be relaxed and intermediate input allocation could be examined in addition to capital and labour allocation. Different methods for examining the relative importance of capital versus output distortions could be explored. In addition, more insights could be gained by examining the relationships between distortions and industry-level and firm-level characteristics. These possibilities are discussed in more detail throughout the paper.

This next section sets out the methodology. Section 3 discusses the data used in this study. Section 4 presents results. Section 5 concludes.

2 Measuring misallocation

This section outlines the methodology developed by Hsieh and Klenow (2009), incorporating their correction appendix (Hsieh & Klenow, 2013). The HK model is based on Melitz (2003), with monopolistic competition among heterogeneous firms. With this model, I estimate the distortions affecting the marginal products of capital and labour across firms within industries, and the extent to which these distortions lower aggregate TFP. In the absence of distortions, the model implies that the revenue productivity (TFPR) across firms within the same industry should be equalised, so the variation in TFPR is considered to be a measure of distortion-driven resource misallocation within an industry.

This section also outlines decomposition methods that allow further examination of the components behind allocative efficiency. In addition, it discusses the implications of the HK method for the size distribution of firms, and in doing so, relates the HK method to another common measure of resource allocation: the Olley and Pakes (1996) covariance. Finally, it highlights some assumptions of the HK method and discusses how future work could address some its limitations.

2.1 Within-industry misallocation

The basic setup of the model is an economy consisting of hetergeneous firms operating under monopolistic competition. Firms not only have different levels of efficiency, they also face different levels of output and capital distortions. A single final good, Y, is produced by a representative firm that combines the output of S industries using Cobb-Douglas production technology:

$$Y = \sum_{s=1}^{S} Y_s^{\theta_s} \quad \text{where} \quad \sum_{s=1}^{S} \theta_s = 1 \tag{1}$$

and θ_s is the value-added share of industry s.

For industry s, the output is a constant elasticity of substitution aggregate of M_s differentiated products:

$$Y_s = \left(\sum_{i=1}^{M_s} Y_{si}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{2}$$

where σ is the elasticity of substitution between goods.

The output of firm i in industry s is produced according to a standard Cobb-Douglas technology with constant returns to scale:

$$Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s} \tag{3}$$

where A_{si}, K_{si}, L_{si} are, respectively, physical productivity, capital input and labour input of firm i in industry s, and α_s is the capital factor share for industry s.

Each firm faces two types of distortions: capital distortions (τ_K) and output distortions (τ_Y). Output distortions, τ_Y, increase the marginal products of capital *and* labour by the same proportion. Capital distortions raise the marginal product of capital relative to labour. As outlined in Dias et al. (2015) and Ryzhenkov (2015), capital distortions may reflect factors such as a non-competitive banking system that provides favourable loan conditions to certain producers or, financial institutions that are unable or unwilling to provide credit to firms that are highly productive but have no credit history or lack tangible assets for use as collateral. Output distortions could be driven by things such as subsidies to specific producers, regulatory or tax collection enforcement activities that are focussed on the largest and most productive firms, or restrictions on firm size due to limitations in the extent of the market (particularly for less tradable products).[6,7] These market distortions appear in the firm's profit equation as "taxes":

$$\pi_{si} = (1 - \tau_{Y_{si}})P_{si}Y_{si} - wL_{si} - (1 + \tau_{K_{si}})RK_{si} \tag{4}$$

where $P_{si}Y_{si}$ is the value added of the firm, w is the wage rate and R is the cost of capital.

Profit maximisation yields the result that the firm's output price is a fixed mark-up over its marginal cost:

$$P_{si} = \frac{\sigma}{\sigma - 1}\left(\frac{R}{\alpha_s}\right)^{\alpha_s}\left(\frac{w}{1 - \alpha_s}\right)^{1-\alpha_s}\frac{(1 + \tau_{K_{si}})^{\alpha_s}}{A_{si}(1 - \tau_{Y_{si}})} \tag{5}$$

In words, the allocation of resources across firms depends not only on firm TFP levels, but also on the output and capital distortions they face. The first-order conditions also imply that the marginal revenue product of labour is proportional to revenue per unit of labour input and that the marginal revenue product of capital is proportional to the revenue-capital ratio:

$$MRPL_{si} = (1 - \alpha_s)\frac{\sigma - 1}{\sigma}\frac{P_{si}Y_{si}}{L_{si}} = w\frac{1}{1 - \tau_{Y_{si}}} \tag{6}$$

$$MRPK_{si} = \alpha_s\frac{\sigma - 1}{\sigma}\frac{P_{si}Y_{si}}{K_{si}} = R\frac{1 + \tau_{K_{si}}}{1 - \tau_{Y_{si}}} \tag{7}$$

Intuitively, in the absence of distortions, the marginal revenue products of capital and labour would be equal to their respective input prices.[8] So, if all firms face the same input prices, in the absence of distortions, the marginal revenue products of capital and labour will equalise across firms. However, if

[6] Conway and Zheng (2014) uses New Zealand firm-level data to examine the extent of tradability in different industries.

[7] Besides distortions on the prices of inputs, wedges may also be interpreted as a stand-in for all of the costs of hiring factors beyond the market price of the factor itself (ie, frictions). Thus, they may also capture the presence of adjustment costs to varying factors, for example. In the context of my empirical strategy, I cannot separately identify the impact of distortions from frictions, and thus I generally use the term distortion to refer to the combination of both.

[8] In this sense, the HK method is similar in spirit to the Petrin and Levinsohn (2012) measure of allocative efficiency. However, as discussed in Chen and Irarrazabal (2015), in the Petrin and Levinsohn (2012) measure, the reallocation term is measured by the weighted average of *changes* in factor inputs across firms, where weights are the gaps between the firm's marginal product of an input and its cost. Hence, this measure would miss the change in allocative efficiency when both TFPQ and idiosyncratic distortions move in the same direction, so that there are no changes in individual firms' inputs. The HK method focuses on the gaps and their changes, thus nesting the changes in allocative efficiency measured by Petrin and Levinsohn (2012).

there are distortions, then the "after-tax" marginal revenue products of capital and labour will equalise across firms. The "before-tax" marginal revenue products must be higher in firms that face disincentives, and can be lower in firms that benefit from subsidies.

Hsieh and Klenow (2009) distinguish between physical productivity (TFPQ), which measures productivity in terms of real output, and revenue productivity (TFPR), which accounts for the revenue of a firm:

$$TFPQ_{si} = A_{si} = \frac{Y_{si}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}} \tag{8}$$

$$\begin{aligned} TFPR_{si} = P_{si}A_{si} &= \frac{P_{si}Y_{si}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}} \\ &= \frac{\sigma}{\sigma-1}\left(\frac{MRPK_{si}}{\alpha_s}\right)^{\alpha_s}\left(\frac{MRPL_{si}}{1-\alpha_s}\right)^{1-\alpha_s} \end{aligned} \tag{9}$$

The distinction between physical and revenue productivity is important. It is typical to use revenues when estimating production functions, as a measure of physical output is typically not available. Firm-level revenue is deflated using industry-level price deflators, which neglects price variation across firms. The use of firm-specific deflators would yield TFPQ, whereas using an industry deflator gives TFPR. In the context of monopolistic competition, where firms have a degree of market power, the use of revenues instead of physical output means that measured technical efficiency is a mix of true technical efficiency and demand factors. That is, when industry deflators are used, differences in firm-specific prices show up in the firm's measured TFP. The Hsieh and Klenow (2009) method infers the physical output, Y_{si} from the observed output, $P_{si}Y_{si}$, by assuming a CES elasticity of demand.

Industry TFP can now be calculated as:

$$TFP_s = \left\{\sum_{i=1}^{M_s}\left(A_{si}\frac{\overline{TFPR}_s}{TFPR_{si}}\right)^{\sigma-1}\right\}^{\frac{1}{\sigma-1}} \tag{10}$$

where M_s is the number of firms in industry S.

Average industry TFPR is calculated as:

$$\begin{aligned} \overline{TFPR}_s &= \frac{\sigma}{\sigma-1}\left[\frac{R}{\alpha_s\sum_{i=1}^{M_s}\frac{1-\tau_{Y_{si}}}{1+\tau_{K_{si}}}\frac{P_{si}Y_{si}}{P_sY_s}}\right]^{\alpha_s}\left[\frac{w}{(1-\alpha_s)\sum_{i=1}^{M_s}1-\tau_{Y_{si}}\frac{P_{si}Y_{si}}{P_sY_s}}\right]^{1-\alpha_s} \\ &= \frac{\sigma}{\sigma-1}\left(\frac{\overline{MRPK}_s}{\alpha_s}\right)^{\alpha_s}\left(\frac{\overline{MRPL}_s}{1-\alpha_s}\right)^{1-\alpha_s} \end{aligned} \tag{11}$$

Equation 10 implies a negative relationship between the degree of dispersion of firms' TFPR within an industry and the degree of inefficiency in the industry TFP. In the special case where there are output distortions and the distributions of firm TFPQ and TFPR are jointly log-normal, the negative effect of distortions on aggregate TFP can be summarised by the variance of log TFPR, which reveals the extent of misallocation due to the dispersion of marginal products.[9] Intuitively, in the absence of distortions, more capital and labour would be allocated to firms with higher TFPQ to the point where their higher output results in a lower price and the exact same TFPR as in firms with lower TFPQ.

In the absence of distortions, the "efficient" industry TFP is given by the CES aggregate of each individual firm's TFPQ:

$$TFP_s^* = \overline{A}_s = \left(\sum_{i=1}^{M_s} A_{si}^{\sigma-1} \right)^{\frac{1}{\sigma-1}} \tag{12}$$

2.2 Aggregate TFP and efficiency gains

The model has a homogeneous final consumption good produced by a representative firm in a perfectly competitive final goods market. This firm combines intermediate goods, Y_s produced by the s industries. These intermediates are aggregated to produce the final good using a Cobb-Douglas production technology, which implies:

$$Y = \prod_{s=1}^{S} Y_s^{\theta_s} = \prod_{s=1}^{S} \left(TFP_s K_s^{\alpha_s} L_s^{1-\alpha_s} \right)^{\theta_s} \tag{13}$$

where Y is aggregate value added, S is the number of industries and θ_s is the share of industry s in aggregate output.

And aggregate TFP is:

$$TFP = \prod_{s=1}^{S} TFP_s^{\theta_s} = \prod_{s=1}^{S} \left[\sum_{i=1}^{M_s} \left(A_{si} \frac{\overline{TFPR}_s}{TFPR_{si}} \right)^{\sigma-1} \right]^{\frac{\theta_s}{\sigma-1}} \tag{14}$$

Finally, the relative gains from efficiency improvements within industries can be expressed as the ratio of actual and "efficient" aggregate productivity:

$$\frac{TFP}{TFP^*} = \prod_{s=1}^{S} \left[\sum_{i=1}^{M_s} \left(\frac{A_{si}}{A_s} \frac{\overline{TFPR}_s}{TFPR_{si}} \right)^{\sigma-1} \right]^{\frac{\theta_s}{\sigma-1}} \tag{15}$$

And the efficiency gains from eliminating resource misallocation are calculated as:

$$\%\ \text{gain} = \left(\frac{TFP^*}{TFP} - 1 \right) * 100 \tag{16}$$

[9]Hsieh and Klenow (2013) show that under additional assumptions, this also holds if there are both output and capital distortions.

2.3 Key parameters

In order to measure the effects of resource misallocation, some key parameters need to be set: the elasticity of substitution (σ), the rental price of capital (R) and the capital share (α_s). In addition, because firm-level prices are not observed in the dataset, firm-specific distortions and productivity must be backed out from available data.

The elasticity of substitution parameter, σ, is set to 3, as it is in the majority of the literature that applies the Hsieh and Klenow (2009) method. Hsieh and Klenow (2009) motivated this choice by concluding that the relevant literature provides estimates of ranging from 3 to 10. As a robustness check, estimates using $\sigma = 5$ are presented in Appendix A.

R is set to 10%, roughly corresponding to a 5% real interest rate and a 5% depreciation rate. Note that the value of R does not affect the gains from efficiency calculation, nor does it affect the relative comparison between firms in a given industry. However, it does affect the average capital distortion.

The capital share, α_s is set to the capital share of the corresponding industry in the United States. As discussed in Hsieh and Klenow (2009), these elasticities are not set to New Zealand capital shares because of the potential importance of distortions in New Zealand, and the inability to separately identify the average capital distortion and the capital production elasticity in each industry. Therefore, US shares are adopted as the benchmark under the presumption that the US is comparatively undistorted.

Since the physical output, Y_{si}, is not observed in the data, distortions and the physical productivity of firms must be expressed in terms of revenue $P_{si}Y_{si}$:

$$1 + \tau_{K_{si}} = \frac{\alpha_s}{1-\alpha_s}\frac{wL_{si}}{RK_{si}} \tag{17}$$

$$1 - \tau_{Y_{si}} = \frac{\sigma}{\sigma-1}\frac{wL_{si}}{(1-\alpha_s)P_{si}Y_{si}} \tag{18}$$

$$TFPQ_{si} = A_{si} = \kappa_s \frac{(P_{si}Y_{si})^{\frac{\sigma}{\sigma-1}}}{K_{si}^{\alpha_s}L_{si}^{1-\alpha_s}} \tag{19}$$

where $\kappa_s = \frac{(P_sY_s)^{\frac{-1}{\sigma-1}}}{P_s}$ is a scaling constant that does not affect within-industry reallocation gains, and is therefore set to 1. Note, however, that κ varies by industry and also over time.

2.4 Decomposition analysis

In order to better understand the forces driving aggregate TFP, I use the decomposition method of Chen and Irarrazabal (2015) and Ryzhenkov (2015). To this end, I assume that A_{si}, $(1-\tau_{Y_{si}})$, and $(1+\tau_{K_{si}})$ are jointly log normal. I approximate the potential gains from optimal resource allocation by applying the Central Limit Theorem to Equation 15:

$$\log TFP^* - \log TFP = \frac{\sigma}{2}\mathrm{var}[\log(TFPR_{si})] + \frac{\alpha_s(1-\alpha_2)}{2}\mathrm{var}[\log(1+\tau_{K_{si}})] \tag{20}$$

The left-hand side represents the gains in Equation 15. On the right-hand side, the variation of TFPR, var(log $TFPR_{si}$), captures resource misallocation across firms, and the variation of capital distortions, var[log(1 + $\tau_{K_{si}}$)], captures the distortions that drive the capital-labour ratio away from the first-best outcome.

In order to further investigate the driving forces of the time variation in the TFPR dispersion, I decompose var(log $TFPR_{si}$) into:

$$\begin{aligned} \text{var}(\log TFPR_{si}) &= \text{var}[\log(1-\tau_{Y_{si}})] + \alpha_s^2 \text{var} \log(1+\tau_{Y_{si}}) \\ &\quad - 2\alpha_s \text{cov}[\log(1-\tau_{Y_{si}}), \log(1+\tau_{K_{si}})] \end{aligned} \tag{21}$$

where the first term on the left-hand side captures the resource misallocation due to output distortion, the second term is due to capital distortion and the third term is the covariance between the two. An efficient resource allocation implies a value of zero for the variance of $TFPR$ and each of the components on the right hand side of Equation 21.

Plugging 21 into 20 gives a decomposition of TFP gains into the variation of the output wedge, variation of the capital wedge, and the covariance between the two:

$$\begin{aligned} \log TFP^* - \log TFP &= \frac{\sigma}{2}\text{var}[\log(1-\tau_{Y_{si}})] + \frac{\alpha_w^2(\sigma-1)+\alpha_s}{2}\text{var}[\log(1+\tau_{K_{si)}}] \\ &\quad - \sigma\alpha\text{cov}[log(1-\tau_{Y_{si}}, log(1+\tau_{K_{si}})] \end{aligned} \tag{22}$$

Again following Chen and Irarrazabal (2015), I quantify changes in resource allocation among firms with different levels of physical productivity. I classify firms into quartiles based on their physical productivity in each year and decompose the variance of log TFPR into between- and within-group variation:

$$\begin{aligned} \text{var}\log(TFPR_{si}) &= \underbrace{\frac{1}{M_s}\sum_q^Q \sum_i^{N_q} (\log TFPR_{sqi} - \overline{\log TFPR_s})^2}_{\text{overall variation}} \\ &= \underbrace{\frac{1}{M_s}\sum_q^Q N_q \text{var}(\log TFPR_{si})_q}_{\text{within-group component}} + \underbrace{\frac{1}{M_s}\sum_q^Q N_q(\overline{\log TFPR_{sq}} - \overline{\log TFPR_s})^2}_{\text{between-group component}} \end{aligned} \tag{23}$$

where log $TFPR_{sqi}$ is the log of TFPR for firm i that belongs to the q^{th} TFPQ quintile in the s industry; $\overline{\log TFPR_s}$ is the mean of log $TFPR$ for industry s; and $\overline{\log TFPR_{sq}}$ is the mean of log $TFPR$ for the q^{th} TFPQ quintile within industry s. Similar to the aggregate TFP decomposition, Equation 23 suggests that, over time, changes in allocative efficiency both within and between groups originate from changes in the gap between actual and efficient resource allocation, given the distribution of physical productivity. Output and capital distortions can also be decomposed using the same within- and between-group approach.

2.5 The size distribution and the Olley-Pakes covariance measure

As outlined in Chen and Irarrazabal (2015), TFPQ and firm-level distortions jointly determine the distribution of firm size (where a firm's size is its level of value added). This has implications for the size distribution of firms. These calculations also shed some light on the relationship between the Hsieh and Klenow (2009) measure and another common measure of allocation: the Olley and Pakes (1996) covariance term. In essence, both methods imply that more productive firms should be larger.

In the HK model, the distribution of firm size translates into a distribution of firm output. Since $Y_{si} = Y_s \left[\frac{P_s}{P_{si}}\right]^{\sigma}$:

$$P_{si}Y_{si} = Y_{si}^{1-\frac{1}{\sigma}} P_s Y_s^{\frac{1}{\sigma}} \tag{24}$$

Since $\sigma \geq 1$, Equation 24 implies that larger firms should have higher output. Moreover:

$$Y_{si} = \left[\frac{A_{si}^{\sigma}(1-\tau_{Y_{si}})^{\sigma}}{(1+\tau_{K_{si}})^{\alpha_s\sigma}}\right] \left(\frac{\sigma-1}{\sigma}\right)^{\alpha} \left(\frac{\alpha_s}{R}\right)^{\alpha_s\sigma} \left(\frac{1-\alpha_s}{w}\right)^{\sigma(1-\alpha_s)} Y_s \tag{25}$$

Substituting Equation 25 into Equation 24:

$$P_{si}Y_{si} \propto \left[\frac{A_{si}(1-\tau_{Y_{si}})}{(1+\tau_{K_{si}})^{\alpha_s}}\right]^{\sigma-1} \tag{26}$$

In words, if there are no distortions, more productive firms tend to be larger. If A_{si} and $1-\tau_{Y_{si}}$ are negatively correlated, more (less) productive firms tend to be smaller (larger) than their efficient size. Likewise, if A_{si} and $1+\tau_{K_{si}}$ are positively correlated, more (less) productive firms tend to be smaller (larger) than their efficient size.

Equation 26 suggests that, over time, a shift in the size distribution is driven by changes in the distribution of both physical productivity (TFPQ) and the firm-level distortions, which determine the efficient size distribution and the gap between the efficient and actual size distributions, respectively. For example, a faster growth (relative to the industry average) of initially less productive firms would result in a thinner left tail of the efficient size distribution, whereas a larger fall in firm distortions for the less productive firms would shift the actual size distribution closer to the efficient one.

In reality, apart from firm distortions,the distribution of TFPR may result from other frictions, such as overhead labour, quasi-fixed capital, firm-level demand and cost factors. Therefore, I also compute the Olley-Pakes covariance between TFPR and activity share as an alterative measure of misallocation as the prediction that more productive firms should be larger is robust to a wide range of models (Bartelsman, Haltiwanger & Scarpetta, 2013). The presence of firm capital and output wedges, as implied by Equation 25, essentially adds noise to the profitability of firms and thus reduces the correlation between productivity and size.

2.6 Assumptions, limitations and extensions

This subsection outlines some assumptions and limitations of the HK method, and highlights some possible extensions that could be incorporated into future work. These include: relaxing the constant-returns-to-scale assumption, incorporating intermediate input reallocation and considering alternative decomposition methods.

Due to the Cobb-Douglas assumption, the only source of inefficiency in the HK model is within-industry misallocation. This implies that an increase in an industry's productivity is fully compensated by a decrease in its price index, so firms' idiosyncratic distortions do not affect the industry composition of the economy. In addition, it is assumed that the number of firms in each industry will not be affected by the extent of misallocation.[10]

The original HK model assumes constant returns to scale. Extending the method to allow for non-constant returns to scale, and using Levinsohn and Petrin (2003)'s method to estimate production functions, Gong and Hu (2016) estimate that manufacturing industries in China have, on average, decreasing returns to scale. They find that relaxing the constant-returns-to-scale assumption in the HK model lowers the estimates of the extent of misallocation in China. For New Zealand data, Cobb-Douglas fixed-effects production function regressions estimate returns to scale of about one on average, which suggests this may not be a large issue. However, for New Zealand, returns to scale do vary somewhat by industry, and may differ if alternative production estimation methods are used (in particular, structural methods such as Ackerberg, Caves and Frazer 2015 or Levinsohn and Petrin 2003). Future work may involve estimating production functions using structural approaches to obtain factor shares rather than using US factor shares, and applying Gong and Hu (2016)'s extension of the HK method.

The original model also does not account for the reallocation of intermediate inputs. Therefore, Dias et al. (2015) extend the model to incorporate intermediate inputs. While they find that capital distortions were the most important source of potential efficiency gains in Portugual during the 1996-2011 period, intermediate input allocation also made an important contribution to the deterioration in allocative efficiency. Benkovskis (2015) applies this extended method to Latvian data and finds that misallocation is notably higher under the original two-factor HK model than the extended model and that the two methods give different misallocation trends over time. That is, the inclusion of intermediate inputs may potentially have a sizable impact on the results. As such, future work is likely to apply this extension to New Zealand data.

Almost all papers that apply the HK method set the elasticity of substitution equal to three (ie, $\sigma = 3$) for all industries in the base case estimates. While the choice of σ does impact on the level of misallocation, it does not generally impact on the changes to misallocation over time. However, since the choice of σ changes the estimated level of misallocation, if σ differs by industry, the assumption that it

[10]Hsieh and Klenow (2009) note that the number of firms would be unaffected by the extent of misallocation in a model of endogenous entry where entry costs take the form of a fixed amount of labour.

is the same across all industries may be problematic for comparisons of industry or sector misallocation levels. Benkovskis (2015) takes an alternative approach of estimating σ for each industry, and finds that σ for a typical Latvian industry is close to 6.5 and that this value varies across industries.

Finally, the decomposition analysis outlined in Section 2.4 relies on the assumption that A_{si}, $(1-\tau_{Y_{si}})$ and $(1+\tau_{K_{si}})$ are jointly log normal. This assumption may not be met in practice. Future work may involve further testing of this assumption and consideration of its importance, including comparing the results from these decompositions to other methods that do not rely on this assumption (for example, the approach of Dias et al. 2015 and Benkovskis 2015).

3 Data

This paper uses data from the Longitudinal Business Database (LBD) component of Statistics New Zealand's Integrated Data Infrastructure (IDI), which contains a wide range of administrative and survey information on New Zealand businesses.[11]

The population of the LBD is all economically significant businesses. LBD contains financial data from the year ending March 2000 to the year ending March 2012. I use an annual panel of enterprises ("firms").[12] I refer to years by their end date (2000 to 2012). For consistency, I do not use production data for the year 2000 (for details see Fabling and Maré 2015b).

I restrict the analysis to industries that are part of what Statistics New Zealand refers to as the "measured sector". The measured sector includes industries which are identified as mainly containing firms that are market producers (Statistics New Zealand, 2016). I further restrict the analysis to private sector, for-profit firms.

The analysis is run on 45 industries. The level of industry disaggregation is chosen based on the availability of suitably disaggregated industry price indices and an adequate number of firms for each industry-year combination. I follow Fabling (2011) and repair firm number links using plant-level employment information. I also assign each firm to one predominant permanent industry over its lifetime as outlined in Fabling and Maré (2015b).

Although the population of the LBD is all economically significant firms, the resulting dataset is not necessarily representative of all firms in the measured sector. This is due to limitations of data availability and coverage, especially for smaller firms (for details see Fabling and Maré 2015b and Fabling and Sanderson 2016).

I draw information from two main sources within the LBD: the Annual Enterprise Survey (AES) and IR10 tax forms. The preferred source of value-added measures is AES as this information is collected by Statistics New Zealand for the purpose of the production of National Accounts. The AES is a postal sample survey, supplemented with administrative data from tax sources. I use postal returns from AES to provide annual gross output and factor inputs for each firm's financial year. This information is available for around 10% of firms, but these are disproportionately larger firms, accounting for around 50% of total employment in New Zealand. Where AES information is not available, I derive comparable measures from annual tax returns (IR10s).

Measures of value added, capital input and labour input are used. Value added is gross output less intermediate inputs. Capital input is measured as the average of opening and closing book value of fixed

[11] For further information about the LBD, see Fabling and Sanderson (2016). For more information about the derivation of production variables from LBD, see Fabling and Maré (2015b).

[12] A business is economically significant if it a.) has annual Goods and Services Tax (GST) turnover of more than $30,000; b.) has paid employees; c.) is part of an enterprise group; d.) is part of a GST group; e.) has more than $40,000 income reported on tax form IR10; *or* f.) has a positive annual GST turnover and has a geographic unit (ie, plant) classified to agriculture or forestry.

capital.[13,14] Each output and input component is deflated to 2007 prices. Gross output is deflated using industry producer output prices, intermediate inputs are deflated using industry producer input prices, wages are deflated using private sector labour costs and capital is deflated using the capital goods price deflator.[15]

Labour input is measured as the sum of full-time-equivalent employees (FTEs) and working proprietors. Hours information is not available in LBD, and the measure of FTEs is therefore derived from the number of employees and information on wages and the number of jobs held using the method developed by Fabling and Maré (2015a). That is, the FTE measure partially, but not completely, adjusts for the likely hours worked.

The wage rate is measured as the total wage/salary bill divided by labour input. The wage/salary bill measure does not include additional benefits that form part of labour compensation (such as superannuation payments). In New Zealand, this is likely to be less problematic than in other countries as New Zealand labour compensation tends to include a comparatively small non-wage component due to a relatively neutral labour income tax system. However, it may be that the non-wage compensation component has increased over time due to the introduction of a subsidised voluntary superannuation scheme (KiwiSaver) in 2007. An additional, likely larger issue, is that labour compensation may not adequately account for the labour input of working proprietors. New Zealand has a high proportion of small firms with working proprietors. While some working proprietors pay themselves a wage/salary, many receive other forms of working-proprietor income. Moreover, regardless of the form of payments to working-proprietor, these payments are most likely to be structured to minimise tax liabilities rather than reflecting working-proprietor labour input to the firm.

This issue of working-proprietor labour input reflects a broader issue with working-proprietor-only firms, where measured capital and labour input are likely to reflect tax rules and suffer from greater measurement error. Due to these issues, only firms with non-zero employment are included in the analysis (ie, working-proprietor-only firms are excluded). Despite this restriction, the data used includes much smaller firms than much of the existing international literature in this area, where the analysis is often restricted to larger firms with more than 10 or 20 employees.

Hsieh and Klenow (2009)'s original paper and many subsequent papers that apply their method use the firm's total wage bill rather than its employment as the preferred measure of labour input. Hsieh and Klenow (2009) argue that using wages per worker adjusts for firm differences in hours worked and worker skill levels. However, they note that wages could also reflect rent sharing between the firm and its

[13] For New Zealand, the use of book values can be justified on the basis that asset-specific tax depreciation rates are intended to align with economic depreciation rates (Fabling & Sanderson, 2016).

[14] Fabling and Maré (2015b) measures capital services as the average of opening and closing book value multiplied by a 10% user cost of capital less reported depreciation plus rental, hiring and leasing costs (since ideally all capital services, whether derived from rented or owned capital, should be included). This approach is not taken here as the Hsieh and Klenow method separately identifies R and K.

[15] Whole-economy labour costs and capital goods price deflators are used as industry-level deflators are not available for capital goods, and only available from 2009 for labour costs.

workers, in which case the differences in TFPR across firms (and therefore, their measure of misallocation) measured using wages for labour input could be understated because the most profitable firms have to pay higher wages. Surprisingly, Hsieh and Klenow (2009) find that using employment as the labour input tends to decrease the reallocation gains in China and India, suggesting that wage differences tend to amplify TFPR differences rather than limit them. I use the number of FTEs plus working proprietors as my preferred labour input measure because the use of FTEs will at least partially account for differences in hours worked. In addition, there is evidence that more successful firms (both internationally and in New Zealand) do pay a firm-wage premium (over and above the worker-wage premium) (for example, see Maré, Sanderson and Fabling 2014 and Card, Cardoso, Heining and Kline 2016). However, I use wages as an alterative labour input measure as a robustness test (see Appendix A).

For the industry-level factor shares, I use US factor shares published by the Bureau of Economic Analysis. Industry classification is different in the two countries - the United States data uses NAICS and the New Zealand data uses ANZSIC06 - so I make an approximate concordance between the two classifications.

I do two-stages of data trimming. In the first stage, firms with non-positive values for gross output, capital inputs, labour input, intermediate inputs or value added are dropped.[16] In addition, observations with log changes in gross output, capital, labour or intermediate inputs of greater than 4 that arise from value changes of more than \$50,000 for financial variables and more than 20 for employment (to allow for plausibly large growth rates for small firms).

In the second stage, most existing literature trims the 1% tails of the distributions of $\log(TFPR_{si}/\overline{TFPR}_s)$ and $\log(A_{si}/\overline{A}_s)$ for each year and then recalculates the relevant variables. However, this approach would eliminate about a third of the value added in each year for my dataset. This large proportion of value added is because firms in the top 1% of the distribution are on average, several times larger than the other firms.[17] This also suggests that their high TFPR may not simply be due to measurement error. In addition, such trimming would fall unevenly across industries, with some industries losing more than 20% of all observations. Therefore, I take an alternative approach. Like Oberfeld (2013), I identify the 1% tails of $\log(MRPK_{si}/\overline{MRPK}_s)$ and $\log(MRPL_{si}/\overline{MRPL}_s)$. Although this results in a smaller reduction in the dispersion of $log(TFPR_{si}/\overline{TFPR}_s)$ and $log(A_{si}/\overline{A}_s)$ compared with trimming on the basis of these two variables directly, it results in the loss of at most 2.5% of value added in any given year. In addition, rather than trimming these tails, I follow Oberfeld (2013) and winsorize the tails. That is, if a firm's $log(MRPK_{si}/\overline{MRPK}_s)$ falls in the top 1% of the distribution, its capital stock in that year is replaced so that its new value of $log(MRPK_{si}/\overline{MRPK}_s)$ is at the 99th percentile. All relevant variables are then

[16]Dropping firms with legitimately negative value added may bias the results. However, as discussed in Section 2, future work will likely use the Dias et al. (2015) extension of the HK method. This extension includes intermediate input reallocation, and consequently, it uses gross output rather than value added for the output measure and therefore also solves the issue of firms with negative value added.

[17]This issue is likely to be larger in the case of New Zealand than in overseas studies because of the inclusion of much smaller firms in my dataset.

recalculated.

Although the analysis is undertaken for 45 industries, most results will be aggregated up to the total or sector level. Three main sectors are examined: the primary sector, the goods-producing sector and the services sector. The manufacturing sector is a subset of the goods-producing sector, but separate results for manufacturing are presented because most international literature focuses on manufacturing firms.[18]

Note that due to different industry, firm and time coverage as well as differences in the trimming method, the results from this paper are not directly comparable to the results of other papers using the Hsieh and Klenow method. As discussed in Fabling and Sanderson (2014), international comparisons can be problematic and should be interpreted with caution.[19] However, where appropriate, some broad comparisons to existing international literature are drawn.

The final sample has about 83,000 to 99,000 firms a year. The services sector accounts for the majority of firms in the sample, with the proportion rising from about 55 percent in 2001 to about 59 percent in 2012. The goods-producing sector accounts for about 23 percent of firms in 2001, rising slightly to 25 percent in 2012. The number of manufacturing firms, which is a subset of the goods-producing sector, decreased in absolute terms, from about 8,800 firms (11 percent) to 8,200 firms (10 percent). The number of primary sector firms in the sample also decreased from about 18,000 firms (22 percent) to 15,000 (18 percent) (Table 1).

[18]The primary sector consists of agriculture, forestry, fishing and mining industries (ANZSIC06 A and B). The goods-producing sector consists of manufacturing, construction and utilities industries (ANZSIC06 C, D and E). The services sector consists of market services (ANZSIC06 F-LL1, M, N, R and S). Manufacturing is a subset of the goods-producing sector (ANZSIC06 C).

[19]The growth of international distributed firm microdata projects reflects the desire to make cross-country firm microdata as comparable as possible while adhering to individual country's data confidentiality requirements. Examples include the OECD's MultiProd project and the European Central Bank's Competitiveness Network Research.

Table 1: Number of firms by year and sector[a,b]

Year	Primary	Goods-producing	Services	Manufacturing[c]	Total
2001	18,270	18,594	45,672	8,784	82,536
2002	17,940	18,906	46,575	8,880	83,418
2003	18,342	20,337	49,437	9,243	88,116
2004	17,946	21,543	51,240	9,483	90,726
2005	17,454	22,737	53,169	9,603	93,357
2006	16,707	24,099	54,486	9,783	95,295
2007	16,380	24,762	55,344	9,627	96,489
2008	16,002	25,716	56,961	9,654	98,682
2009	14,652	24,876	55,935	9,282	95,460
2010	15,354	23,100	54,501	8,874	92,952
2011	14,307	22,497	54,441	8,637	91,242
2012	14,811	21,621	53,001	8,181	89,436

[a] 'Total' column is the sum of 'Primary', 'Goods-producing' and 'Services' columns. All figures are randomly randomed to base 3, in accordance with Statistics New Zealand confidentiality requirements. Columns may not add to total due to rounding.
[b] See Footnote 18 for details of the industries included in the primary, good-producing and services sectors.
[c] 'Manufacturing' is a subset of the 'Goods-producing' sector. It is included as a separate category because the majority of papers in this area focus on manufacturing.

4 Results

This section presents the results from applying the HK method to New Zealand data, by sector and over time. It then looks at the Olley-Pakes covariance as an alternative measure of allocation. It summarises the HK and Olley-Pakes measures and looks at the results before and after the Great Recession. It also compares the importance of within-industry allocation and between-industry allocation. Then, the HK results are presented by industry, and some implications of the HK results for the firm size distribution are drawn. Finally, the results are decomposed into contributions from output and capital distortions.

4.1 HK results: Summary and sector comparisons

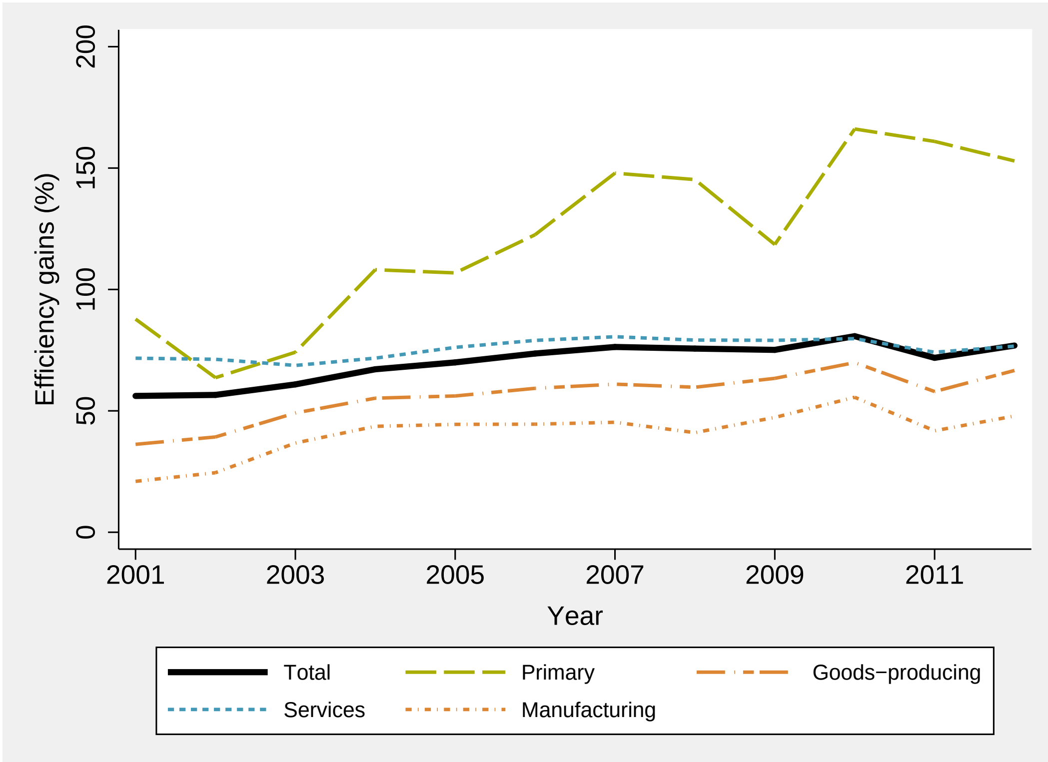
This sub-section presents the main results from applying the HK method to New Zealand firm data. I find that potential TFP gains in the total measured sector from reallocation increased over the 2000s. While TFP could have been around 56 percent higher in 2001, this figure increased to 77 percent by 2012 (Figure 2).

The potential gains vary by sector (Figure 2). Potential TFP gains are by far the highest in the primary sector (average of about 121 percent over the 2001–2012 period), followed by the services sector (average of 76 percent), and were lowest in the goods-producing sector (average of 56 percent). Isolating the manufacturing part of the goods-producing sector, potential gains were even lower than in the overall goods-producing sector (average of 41 percent).[20]

While the potential gains from within-industry allocative efficiency seem large, in terms of broad magnitudes, they are in line with existing studies that apply the Hsieh and Klenow method to data from various countries. Most of these international studies focus on manufacturing. For example, Hsieh and Klenow (2009)'s original paper found that potential within-industry allocative efficiency gains in US manufacturing were about 36 percent in 1998, growing to about 43 percent in 2005, and that China and India had significantly higher levels of misallocation, with potential gains of 100–128 percent for India and 87–115 percent for China. Indeed, perhaps unsurprisingly, studies that examine transition and developing economies using the Hsieh and Klenow method generally find that these countries have considerably higher misallocation than the US. For example, Latin American economies (Busso, Madrigal & Pagés, 2013), the Ukraine (Ryzhenkov, 2015), Bolivia (Machicado & Birbuet, 2012) and Thailand (Dheera-Aumpon, 2014). However, this is not generally the case for studies that look at developed countries, with some studies finding a higher degree of misallocation than the US (such as Calligaris 2015 for Italy), while others find a similar or even somewhat lower degree of misallocation. For instance, Bellone and Mallen-Pisano (2013) finds that the level of measured misallocation in France is similar to the US. As a result, they suggest that the HK methodology may be useful for detecting large efficiency gaps between developing and developed

[20] As discussed in Section 2.6, almost all the literature in this area sets σ to 3 across all industries. However, it may be the case that σ varies by industry, which may render comparisons of the level of misallocation across industries and sectors problematic and results should be interpreted with this in mind.

Figure 2: Potential TFP gains from within-industry efficiency improvements over time[a]



[a]Calculated using Equation 16, ie, % gain $= \left(\frac{TFP^*}{TFP} - 1\right) * 100$

countries, but may not do a good job at discriminating between developed countries.[21] As discussed in Section 3, this difficulty is exacerbated by cross-country differences in data.

Bellone and Mallen-Pisano (2013) also suggest extending the HK method to non-manufacturing industries when looking at efficiency gaps across developed countries as market distortions are likely to have a stronger impact in terms of misallocation within service industries than within manufacturing industries. This would also be consistent with industry-level studies which suggest that cross-country differences in productivity can mainly be traced to service industries rather than goods-producing industries (for example, Inklaar, Timmer and van Ark 2007).

To date, very few studies have applied the HK method to non-manufacturing industries. Two exceptions are studies on Spain (García-Santana et al., 2016) and Portugal (Dias et al., 2015). Both studies find that misallocation is higher in non-manufacturing sectors. For Portugal, manufacturing gains were between 38 and 54 percent, compared with between 57 and 82 percent in agriculture and 58 to 92 percent in services. For Spain, manufacturing gains were about 23 percent to 32 percent, compared with 36 to 62 percent in construction, 38 to 48 percent in trade and 40 to 54 percent for services. Once again, while

[21]Bellone and Mallen-Pisano (2013) note that an alternative explanation is that the allocative efficiency is indeed close in France and the US, which would challenge the established view that Contential European economies have higher input and output distortions than the US economy.

these seem to be fairly similar in broad order of magnitude to the results for New Zealand, it is difficult to make direct comparisons.

4.2 HK results: Trends over time

The results from applying the HK method in Figure 2 are the hypothetical increases in the level of aggregate TFP that would result from fully equalising TFPR in each industry. However, as acknowledged by Hsieh and Klenow (2009), these counterfactuals do not allow for measurement error or model misspecification. If one focuses on the change in potential TFP gains over time, rather than the level, this implies a less stringent assumption that neither measurement error nor model misspecification have increased over time.

For New Zealand, potential TFP gains have increased over time in all sectors. Services had the smallest increase (from 72 percent in 2001 to 77 percent in 2012), albeit from a higher initial value than the goods-producing sector. The primary sector increased from 89 percent in 2001 to 153 percent in 2012. The goods-producing sector increased from 36 percent in 2001 to 67 percent in 2012. Potential TFP gains in the manufacturing sub-sector more than doubled, albeit from a comparatively low base, from 21 percent in 2001 to 48 percent in 2012.

This increasing level of misallocation over time seems to a fairly common (although not universal) finding in the international literature for developed countries. For example, García-Santana et al. (2016) and Dias et al. (2015) find increasing misallocation across all sectors in Spain and Portugal respectively, and Calligaris (2015) finds increasing within-industry misallocation for Italy's manufacturing sector. In contrast, for transition economies such as the Ukraine (Ryzhenkov, 2015) and developing countries, such as China (Hsieh & Klenow, 2009), existing literature generally finds improvements in allocative efficiency over time.

The finding of decreasing misallocation in transition and developing economies and is perhaps unsurprising given liberalisation, improvements in regulatory frameworks and financial sector development. However, the factors behind increasing misallocation in developed countries are less clear. For example, Dias et al. (2015) states that the reasons behind increasing within-industry misallocation among Portuguese firms are not easy to identify. However, the Portuguese study along with others (such as García-Santana et al. 2016 for Spain and Calligaris 2015 for Italy), suggest that distortions are greater among small and young firms. In addition, the importance of capital distortions is increasing among Portuguese and Spanish firms, suggesting that the financial sector may have contributed to the survival of many small and relatively inefficient firms. This is also consistent with other strands of literature (such as Barnett et al. 2014 and Gopinath et al. 2015 as discussed in Section 1).

There does seem to be an unusual element to the New Zealand trends over time, however. Specifically, it seems to be somewhat unusual that New Zealand's degree of misallocation increased during the the expansionary part of the economic cycle in the early part of the 2000s (see Figure 1). García-Santana et al. (2016) even argues that this increase in misallocation during an expansionary period has been "a singular experience of Spain" (p8), as other countries have experienced either no change or improvements in allocative efficiency during expansions.[22] However, in this respect, the Spanish experience has not been unique as the New Zealand results also seem to exhibit this unusual pattern.

García-Santana et al. (2016) argue that their results are consistent with the view that the Spanish expansion, which saw high output despite very poor productivity performance due to large factor accumulation, was due to a demand boom rather than improvements through structural reforms. New Zealand also experienced high output growth despite poor productivity growth in the 2000–2008 productivity growth cycle (Figure 1). In addition, it has been argued that New Zealand experienced "unbalanced", domestic consumption-led growth during this period. To date, the New Zealand debate has focussed on the industry-level consequences of this growth, such as the increasing share of resources going to industries that primarily focus on supplying the domestic economy at the expense of the tradables sector (for example, see New Zealand Treasury 2010, 2012.). However, this may have also had consequences for resource allocation within industries. For example, higher demand during expansions may allow inefficient firms to thrive, leading to greater within-industry misallocation (García-Santana et al., 2016).[23]

For New Zealand, the decompositions presented in Section 4.8 are a first pass at addressing the question of what factors might driving the increasing in misallocation over time. Future work may also provide more insights into this question, for example, by looking at the relationship between distortions and firm- and industry-level characteristics.

4.2.1 The primary sector: A special case?

The New Zealand results for the primary sector warrant some discussion.[24] They show a notably large and increasing degree of misallocation (Figure 2). This might suggest, for example, that resource allocation is particularly sticky in the primary sector as it is difficult for producers with high physical productivity to expand output, and that these difficulties have increased over the examined period. Possible reasons for this may include difficulties securing suitable farm land to expand output, or it might be that the closely-held/family-owned nature of many farming businesses limits the expansion of good performers. It is also notable that agricultural credit increased markedly in this period, accompanied by falling real

[22]For example, Bartelsman et al. (2013) find that allocative efficiency was quite steady over the 1990s and 2000s in several developed countries while it increased in countries where the expansions were driven by significant economic reforms, such as Central and Eastern European countries. In addition, there is evidence of increases in allocative efficiency during expansions in Chile (Chen & Irarrazabal, 2015) and Switzerland (Lewrick, Mohler & Weder, 2014). Declines in allocative efficiency during periods of stagnation and contraction have also been documented, such as Dias et al. (2015) for Portugual.

[23]This is the flip-side of the argument that recessions have a 'cleansing effect', whereby resource allocation improves during recessions because lower demand diminishes rents and forces inefficient firms to exit (Caballero & Hammour, 1994).

[24]Recall that the primary sector consists of agricultural, forestry, fishing and mining industries. However, the following discussion focuses on agricultural production since the vast majority of firms in New Zealand's primary sector are agricultural producers.

interest rates and increasing rural land prices.[25] International work, such as Gopinath et al. (2015), suggests that expanding credit can result in an increase in capital misallocation if, for example, it means that the credit going to low-productivity but high-collateral firms increases relative to the credit going to high-productivity but low-collateral firms.

However, another possibility is that the HK model is not particularly well suited to the characteristics of the primary sector. It is likely that many primary sector producers are price takers.[26] Therefore, the implication of equalisation of revenue productivity across firms within the same industry in the absence of distortions may be less applicable to the primary sector. This is because the mechanism for this implication is that, in the absence of distortions, firms with high physical productivity will attract more labour and capital and increase their output up until the point where revenue productivity equalises across firms. This assumption may be less applicable to the primary sector as it premised on the ability of individual producers to impact prices.

This alternative explanation of price-taking firms may also account for the notable increase in misallocation in the primary sector over time. Commodity prices rose significantly during the examined period. Therefore, it may have been profitable for producers facing higher world prices to increase their output, and this increase in output would have had little or not impact on world prices. This may have resulted in poorer physical productivity outcomes (for example, it may have become profitable to farm more marginal land) and an increase in the dispersion of revenue productivity.

Due to the potential issues of the applicability of the HK model's assumptions, particularly to the primary sector, the next subsection presents the Olley-Pakes covariance as an alternative "model-free" measure of resource allocation. As will be discussed, the Olley-Pakes measure suggests that the increase in misallocation in the primary sector is not just an artefact of the HK model's assumptions.

4.3 Olley-Pakes: An alternative measure

As well as the issue of possible misspecification, a more general issue with the HK method is that changes in the dispersion of TFPR might arise from other frictions apart from idiosyncratic distortions. For instance, differences in firms' TFPR can arise due to overhead labour or quasi-fixed capital (see Bartelsman et al. 2013). I therefore also present the Olley and Pakes (1996) covariances as alternative measures of misallocation.

The Olley-Pakes method involves computing the covariance between firm-specific labour input shares

[25] Based on the Reserve Bank of New Zealand's 'C27 Agricultural credit by registered banks' series, total 'on farm' loans increased from nearly \$18b in 2003 to about \$47b in 2012 (in nominal dollars). Allan and Kerr (2014) shows the large increase in rural land sale price per hectare in New Zealand in the 2000s leading up to the Great Recession.

[26] Apatov, Fabling, Jaffe, Morris and Thirkettle (2015) suggests three reasons why New Zealand agricultural producers may be price takers: 1. much of the output is exported, for example, approximately 95 percent of meat and dairy output produced is exported, and therefore subject to world prices; 2. the vast majority of the industry is comprised of small enterprises; 3. agricultural output tends to be fairly homogenous (keeping in mind that in general, agricultural firms are principally involved in 'behind-the-farm-gate' production, while firms that are principally involved in the processing of agricultural products are classified as manufacturing firms).

and labour productivity, as well as firm-specific production shares and TFP. As discussed in Section 2, there is a link between the HK and Olley-Pakes measures as both methods imply that under an efficient allocation of resources, more productive firms should be larger. An additional advantage of the Olley-Pakes method is that it can be used to investigate both labour productivity and TFP.[27]

The first two columns of Figures 3 and 4 are graphical representations of the Olley-Pakes measures for labour productivity and TFP. These columns show the productivity differences across quartiles of the productivity distribution and production shares by productivity quartile. The production shares are measured using employment in the case of labour productivity and value added in the case of TFP.[28] More specifically, for each quartile of the productivity distribution, the first column shows the average productivity of firms within that industry relative to the overall average firm productivity for that industry. The second column shows the share of employment (value added) for firms in each labour productivity (TFP) quartile. As discussed, the Olley-Pakes measure suggests that the employment (value-added) shares should be larger for higher labour productivity (TFP) quartiles.

However, the Olley-Pakes measure is static, in the sense that it only looks at whether more productive firms are larger at a particular point in time. Intuitively, if there are few or no impediments to reallocation, economies should exhibit the tendency for more productive firms to have faster-than-average growth over time, and for less productive firms to shrink or exit. To get a more dynamic view of these developments, Figures 3 and 4 also show the growth rates of firms by productivity quartiles. Specifically, the third column shows the growth of employment (value added) in firms in each quartile of lagged labour productivity (TFP).

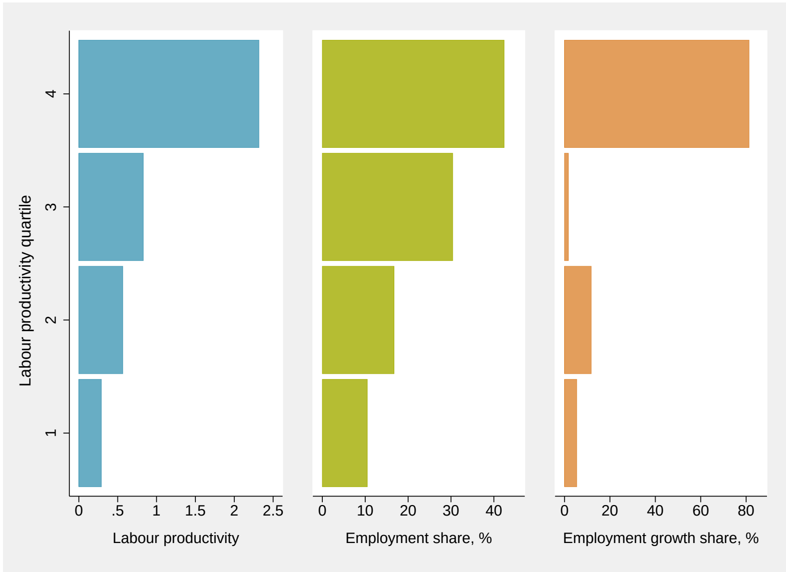
The first column of Figure 3 shows that there is a wide distribution of labour productivity. The top quartile of firms in the labour productivity distribution are about 2.3 times more productive than the average firm, while those in the bottom quartile have productivity that is only about 0.29 of the average. Although it is not possible to compare this distribution directly with results for other countries due to differences in data and coverage, this pattern also appears in other countries, albeit to varying degrees (see for example, Bartelsman 2013).

Turning to the second column of Figure 3, as mentioned, the intuitive interpretation of the Olley-Pakes covariance measure is that more productive firms should have greater market share. Indeed, this is the case in New Zealand, with employment shares monotonically increasing in the productivity quartile (about 10% for the bottom quartile, 17% for the second quartile, 30% for the third quartile and 42% for the top quartile). As Bartelsman (2013) shows, while this pattern is exhibited in several other countries, for some countries such as the UK, the lowest labour productivity quartile actually accounts for the largest share of employment.

[27] I measure labour productivity as revenue labour productivity, ie, value added per worker, where value added is deflated to 2007 levels using industry deflators, as described in Section 3.

[28] The use of value added for TFP is for presentational simplicity. The calculation of the Olley-Pakes covariance, as presented in Figure 5 and Table 2, uses firm-specific production share weights, as described below.

Figure 3: (Re)allocation by labour productivity quartile, all sectors[a b c d]



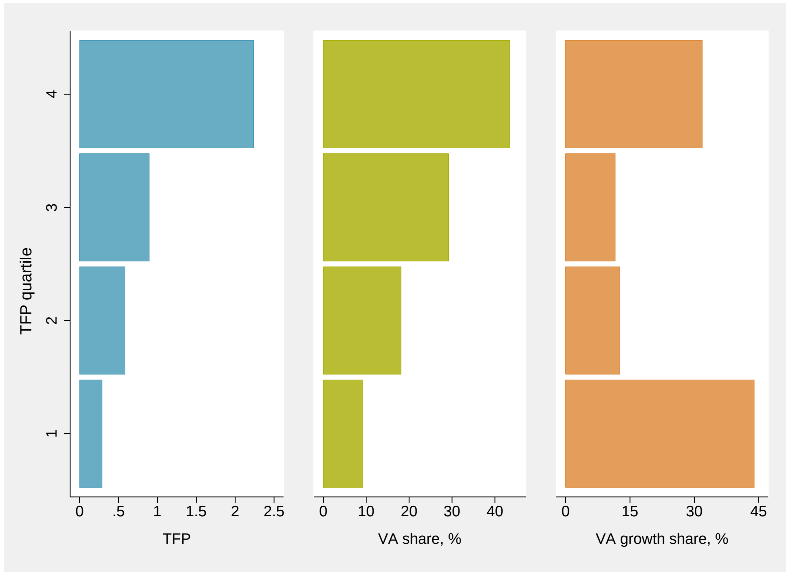
[a]The highest productivity quartile is labeled '4', the lowest '1'.
[b]The horizontal axis for labour productivity measures the average level of productivity for firms within each quartile in the industry relative to the industry unweighted mean, summed over all industries using industry employment weights, and averaged across all years
[c]The horizontal axis for employment share measures the share of employment in firms in each labour productivity quartile (total employment by quartile for all years and industries divided by total employment for all years and industries).
[d]The horizontal axis for employment growth share is total employment growth by quartile for all years and industries divided by total employment growth for all years and industries.

The third column in Figure 3 shows that the top quartile of firms in the labour productivity distribution account for the large majority of employment growth (over 80%). However, the share does not increase monotonically, with the third quartile accounting for about 2% of employment growth, the second quartile for about 12% and the bottom quartile for about 5%.

Figure 4 shows that average TFP by TFP quartiles follows a very similar pattern to labour productivity. The TFP of the top quartile is about 2.2 times larger than average TFP, and the bottom quartile is about 0.29 of the average. Likewise, the share of value added by TFP quartile is very similar to the pattern for labour productivity. Higher TFP quartiles account for a higher share of value added. The bottom quartile accounts for about 9% of value added, and the top quartile accounts for about 43%. The third column of Figure 4 shows that the the bottom quartile of the TFP distribution accounts for more of the growth in value added than any other quartile, and in particular, more than the top quartile (44% versus 32%).

A more formal way to present the results in Figures 3 and 4, as well as investigate changes over time, is via the Olley-Pakes covariance measure. Figure 5 shows that the revenue labour productivity (LPR) and revenue TFP (TFPR) Olley-Pakes covariances over time and by sector. This measure is calculated as the covariance between firm-specific production shares and productivity at the industry level, and these

Figure 4: (Re)allocation by TFP quartile, all sectors[a b c d]



[a]The highest productivity quartile is labeled '4', the lowest '1'.
[b]The horizontal axis for TFP measures the average level of productivity for firms within each quartile in the industry relative to the industry mean, summed over all industries using industry value-added weights, and averaged across all years
[c]The horizontal axis for VA share measures the share of value added in firms in TFP quartile (total VA by quartile for all years and industries divided by total VA for all years and industries).
[d]The horizontal axis for VA growth share is total value-added growth by quartile for all years and industries divided by total employment growth for all years and industries

industry-level results are then weighted up to the sector level.[29]

The labour productivity Olley-Pakes covariance is higher than the TFP covariance. That is, the positive relationship between firm size and productivity is stronger for labour productivity than TFP. For the total measured sector, the labour productivity covariance has increased slightly, while the TFP covariance has decreased. Consistent with the HK measure, the decrease in the TFP covariance occurs across all sectors.

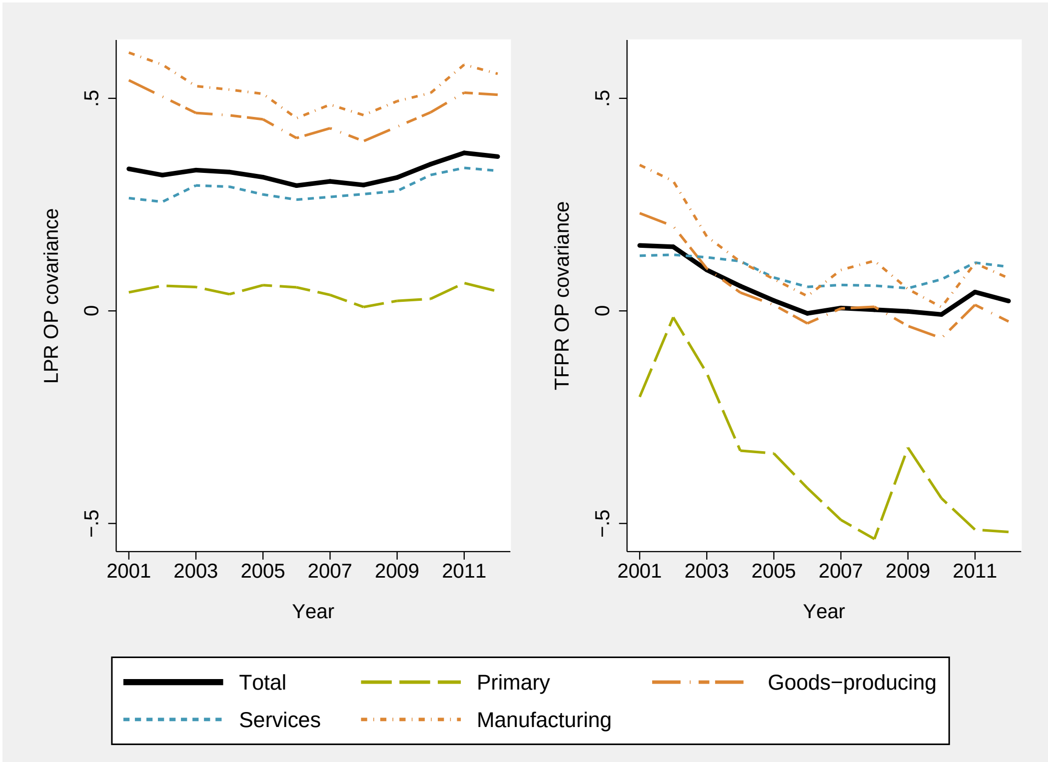
Looking across sectors, the primary sector has noticeably lower covariance than the other sectors for both labour productivity and TFP. This is consistent with the HK measures of misallocation by sector, and suggests the HK results are not just an artefact of the model's assumptions. In fact, the primary sector TFP covariance is negative in all years. The labour productivity covariance is highest for the goods-producing sector (and in particular, the manufacturing sub-sector). However, for TFP, the

[29]To be more precise, for industry j and year t, the covariance for labour productivity is calculated as:

$$OP_{jt} = \sum_i (\theta_{ijt} - \overline{\theta}_{jt})(\omega_{ijt} - \overline{\omega}_{jt})$$

where i is the firm index, ω_{ijt} is the firm-specific productivity, θ_{ijt} is firm-specific employment (ie, labour input) share, and $\overline{\omega}_{jt}$ and $\overline{\theta}_{jt}$ are the unweighted averages of industry j. Industry-level results are then weighted up to sector/total results using industry labour input shares. The same covariance can be computed for TFP using firm-specific production shares, ie, $K_{ijt}^{\alpha_j} L_{ijt}^{1-\alpha_j}$. However, value-added weights are used to weight up from the industry level to the sector-level due to the difficulty of comparing input across industries due to differences in α_j's across industries.

Figure 5: Olley-Pakes covariance over time[a]



[a]See Footnote 29 for details.

services sector has a slightly higher covariance than the goods-producing sector, and the covariance for the services sector is similar to the manufacturing sub-sector. This is inconsistent with the results for the HK measure which suggested that misallocation is worse in the services sector than the goods-producing sector, and further investigation of this may be needed.[30]

4.4 Misallocation and the Great Recession

From Figures 2 and 5, it does not appear to be the case that allocation significantly worsened after the Great Recession in general. Rather, misallocation was increasing even before the Great Recession, and has been increasing fairly steadily over time. There does appear to be an increase in the volatility of misallocation post-Great Recession, but a pattern of sharp increases after 2008 is not evident.

However, to summarise the different measures of allocation by sector and over time, Table 2 presents the annual averages of the Hsieh and Klenow (2009) and Olley and Pakes (1996) for the first part of the 2000s (2001-2008) and for the post-financial-crisis period (2009-2012). These results clearly show that resource allocation has worsened over time across all sectors for the TFP measures (HK and OP TFPR

[30]For example, as discussed in Section 2, this may involve investigating whether the choice of σ, and in particular, setting σ to take the same value across all industries, is driving the the HK result of higher misallocation in the services sector than the goods-producing sector.

columns in Table 2). For the labour productivity Olley-Pakes measure (column OP LPR), there has been little change over time, and even perhaps a slight improvement.

Table 2: Allocation in New Zealand: 2001-2008 vs. 2009-2012

		HK	OP LPR	OP TFPR
Total	2001-2008	67.0	0.32	0.06
	2009-2012	76.2	0.35	0.01
Primary	2001-2008	107.0	0.05	-0.31
	2009-2012	149.6	0.04	-0.45
Goods-producing	2001-2008	52.0	0.46	0.07
	2009-2012	64.5	0.48	-0.03
Services	2001-2008	74.8	74.77	0.10
	2009-2012	77.4	77.39	0.09
Manufacturing	2001-2008	37.6	0.52	0.16
	2009-2012	48.1	0.54	0.06

[a] 'HK' refers to the Hsieh and Klenow (2009) method described in Section 2.
[b] 'OP LPR' refers to the Olley and Pakes (1996) covariance for revenue labour productivity.
[c] 'OP TFPR' refers to the Olley and Pakes (1996) covariance for TFPR.
[d] Measures for the different time periods are calculated as average annual figures.

4.5 Within-industry versus between-industry allocation

There is interest among New Zealand policy circles in the extent to which New Zealand's poor productivity performance is due to poor within-industry performance (which includes within-industry allocation) versus a shift in resources towards low-productivity industries. To inform this question, I present a counterfactual exercise to investigate the importance of between-industry allocation versus within-industry allocation during the 2000s (Figure 6). This exercise involves holding industry value-added shares constant at their 2001 levels over time, and examining what difference this makes to the base case misallocation measure presented in Figure 2.

This exercise suggests that holding industry shares at their 2001 level makes little difference to the potential within-industry efficiency gains. Indeed, holding industry shares constant results in a slightly higher level of potential efficiency gains, suggesting that between-industry reallocation made a small but positive contribution to TFP growth over the 2000s.[31] But, overall, within-industry misallocation appears to be much more important than between-industry reallocation over the 2000–2012 period. However, this

[31] Using data from Statistics New Zealand's LBD, but a different decomposition methodology and estimation strategy for TFP, Maré et al. (2015) also finds that between-industry reallocation made a small but positive contribution to aggregate TFP growth between 2001 and 2012.

does not rule out the possibility that between-industry reallocation would be more important if a longer time period was examined.

García-Santana et al. (2016) undertakes a similar counterfactual exercise, and finds that an increase in within-industry misallocation is more important in explaining Spain's declining TFP than between-industry allocation. However, Oberfeld (2013) offers a more systematic method for assessing the importance of within- versus between-industry allocation, and finds that within-industry allocation remained constant or improved during Chile's 1982 financial crisis, but between-industry allocative efficient declined. Because of the degree of interest in the question of within- versus between-industry allocation, future work may endeavour to provide more robust results by applying Oberfeld (2013)'s method to New Zealand data.

Figure 6: Potential TFP gains with 2001 industry shares[a]

[a]The 'Base case' efficiency gains are those presented in Figure 2. The 'Constant 2001 industry shares' recalculates the efficiency gains assuming that industry shares (θ_s) remain constant at their 2001 level.

4.6 Efficiency gains by industry

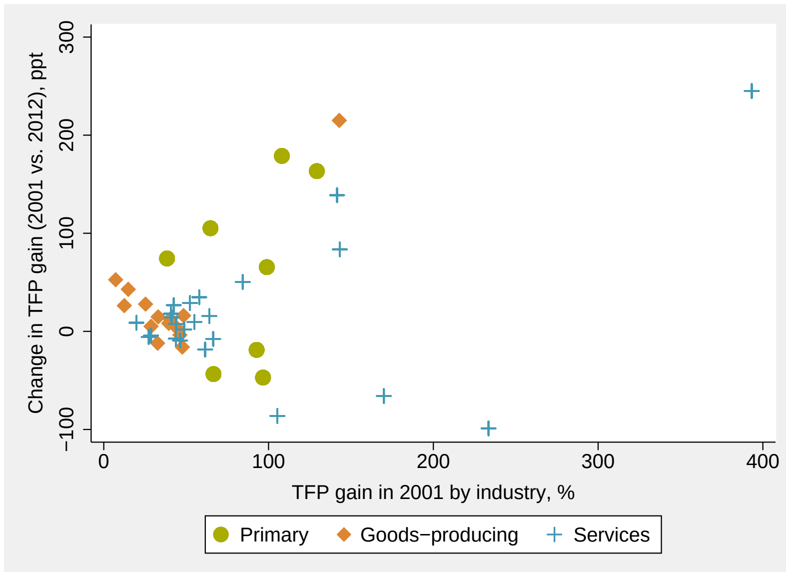
Was the increase in misallocation over the 2000s due to increased misallocation within a few large industries, or due to a general rise in misallocation within most industries? And was there any relationship between the initial level of within-industry misallocation and subsequent changes in misallocation?

Misallocation rose in the majority of industries (30 out of 45), suggesting that the overall deterioration in allocative efficiency between 2001 and 2012 was generalised (Figure 7). Within all sectors (primary, goods-producing and services), misallocation rose in the majority of industries between 2001 and 2012.[32]

[32]Future work may investigate industry contributions to the overall potential efficiency gain results in more detail.

For the manufacturing subgroup of the goods-producing sector, misallocation rose in all industries. In addition, there does not appear to be much of a pattern between initial levels of within-industry misallocation and subsequent changes.

Figure 7: Potential TFP gains: Level and changes by industry



Some international studies have found a link between industry characteristics and the level of, and changes in, industry efficiency gains. For example, García-Santana et al. (2016) explores the relationship between resource allocation and industry-level skill intensity, research and development intensity, tradability, external finance dependence and the degree of regulation in Spain. It finds that most of these factors are uncorrelated with misallocation, however, regulation appears to be important, with industries facing higher degrees of regulation having higher levels of misallocation. Relationships between resource allocation and industry-level characteristics for New Zealand may be explored in further work.

4.7 Implications for the size distribution

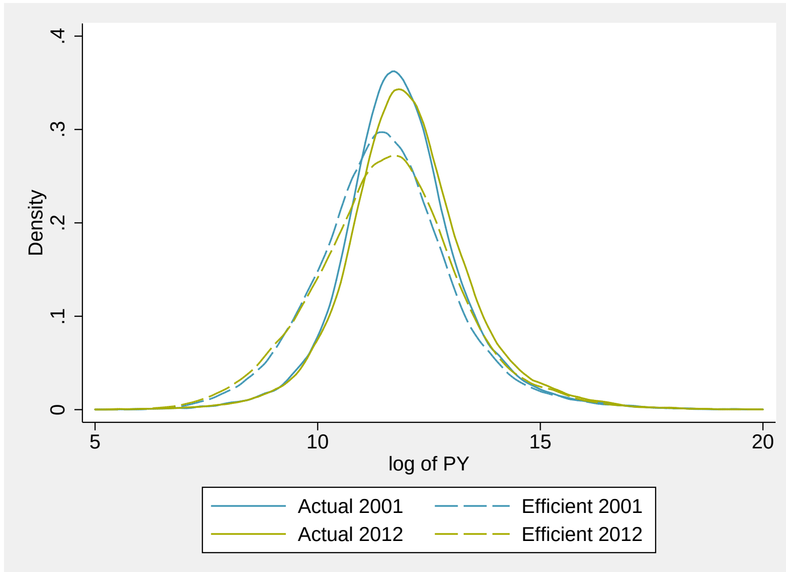
As discussed, Equation 26 suggests that, over time, a shift in the size distribution is driven by changes in the distribution of both physical productivity and idiosyncratic distortions. The distribution of physical productivity determines the efficient size distribution, and the idiosyncratic distortions determine the gap between the actual and efficient size distribution.[33]

Looking first at the efficient size distribution, Figure 8 shows that the efficient size distribution has widened over time, suggesting a deterioration in efficient TFP. It appears that the increase in the efficient size distribution is mostly due to a stretching of the right tail, which suggests that firms with initially

[33]The efficient size is calculated as the level of value added that a firm would have if it had an efficient level of TFPR (where the efficient level of TFPR is given in Equation 11).

higher physical productivity (relative to the industry average) grew faster.[34]

Figure 8: Firm size distribution[a]



[a]Tails of the distribution have been truncated for confidentiality reasons.

Turning to the gap between the actual and efficient firm size distribution, as discussed in Section 2, with the HK method, if A_{si} and $1 - \tau_{Y_{si}}$ are negative correlated, more (less) productive firms tend to be smaller (larger) than the efficient size. Similarly, if A_{si} and $1 + \tau_{K_{si}}$ are positively correlated, more (less) productive firms tend to be smaller (larger) than the efficient size. This implies that when there are distortions, the efficient size distribution is more dispersed than the actual size distribution, and this is indeed what is observed in Figure 8.

Moreover, consistent with the finding of increasing misallocation over time, the correlation between A_{si} and $1 - \tau_{Y_{si}}$ has become more negative over time (from -0.21 in 2001 to -0.25 in 2012). This increasingly negative correlation has occurred across all three sectors. Likewise, the positive correlation between A_{si} and $1 + \tau_{K_{si}}$ has increased over time (from 0.28 in 2001 to 0.30 in 2012).

An interesting feature of Figure 8 is that it suggests that small firms are generally too large given their level of TFPR (or, equivalently, that their level of TFPR is too low given their size). That is, given their level of TFPR, small firms tend to overproduce relative to their efficient level. This result is also found for Chile (Chen & Irarrazabal, 2015), the Ukraine (Ryzhenkov, 2015), Colombia, El Salvador and Mexico (Busso et al., 2013). The general explanation given for this result is that small firms are subsidised (either implicitly or explicitly), for example, through size-contingent policies or less stringent enforcement of tax collection or of other regulations. This argument is more difficult to make for New Zealand, which lacks explicit size-continent policies and where the case that enforcement is more lax for

[34]Using LBD data over the same time period, Zheng (2016) also finds that New Zealand firms with the highest levels of TFP grew faster than other firms in their industry.

small firms is harder to make.[35]

It is possible, however, that there are other distortions (or frictions) that result in small firms being larger than their efficient size.[36] For instance, some commentators note that many small firms in New Zealand are closely-held businesses that may be financed by securing a mortgage against the owners' residential property. That is, small, closely-held businesses may be able to borrow at mortgage rates, which are likely to be lower than business rates due to differences in the risk premia. Or it may be that firms that have low TFPR are able to grow bigger than optimal due to the limited extent of the market and a lack of competition. This ability for firms to grow larger than their TFPR level would dictate also seems to be consistent with the comparatively poor "up-or-out" dynamic among New Zealand firms.[37] In order to investigate these theories further, future work may look at these results by sector and industry in order to assess whether there is a relationship between industry characteristics (such as at the degree of tradability) and the size distribution.

In addition, to gain more insights into the role of firms with different characteristics, including small firms, in the increase in misallocation over time, future work may look at the relationship between distortions and firm characteristics. For example, García-Santana et al. (2016) finds that young and small firms are potential sources of the increase in misallocation in Spain. Similarly, Calligaris (2015) finds that misallocation in Italy is higher among small and young firms, as well as firms located in southern Italy and firms that operate at low-technology intensity. In contrast, Dheera-Aumpon (2014) finds that mid-sized firms face higher distortions than small firms in Thailand. Many of the international studies use repeated cross-sectional, or if the data are longitudinal, do not fully exploit this feature. However, the New Zealand data are longitudinal, and future work may use this feature in order to control for unobserved heterogeneity and to explore the relationship between changes in misallocation, distortions and firm performance over time.[38]

4.8 Decomposing the HK results

I now decomposition the HK measure of misallocation into the contribution of various components under the joint log-normal assumption of physical productivity and idiosyncratic distortions. As noted in Section 2, this is a first pass as quantifying the relative importance of output and capital distortions and future work may explore alternative decompositions methods, particularly ones that do not rely on the jointly

[35]It also appears to contradict the conventional wisdom that New Zealand's productivity growth is hampered by an abundance of small firms and a lack of large firms. However, this is not necessarily the case as this method only examines the efficient size of a firm given its TFPR, and this static measure does not necessarily rule out this possibility.

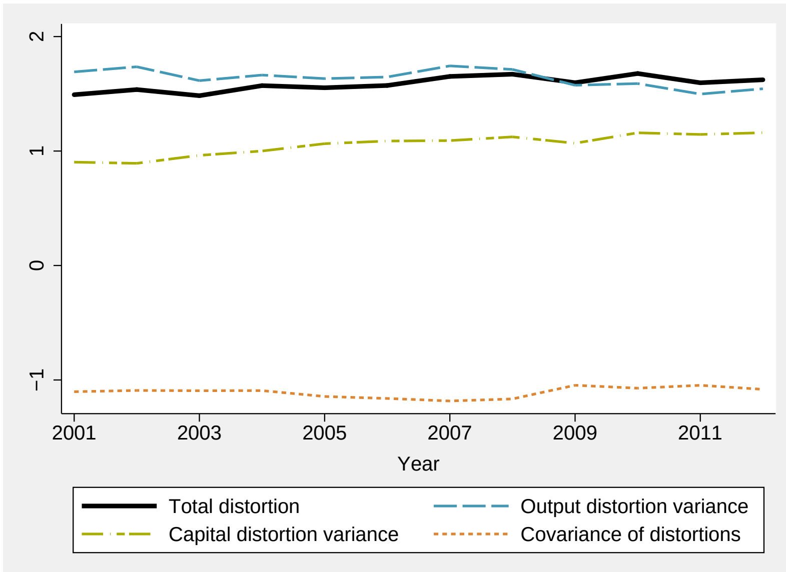
[36]As discussed, in the HK model, any factors that results in a distribution of TFPR is a distortion. That is, it does not allow for the possibility of other frictions that would result in a distribution of TFPR, such as adjustment costs.

[37]For example, Criscuolo et al. (2014) finds that New Zealand has a high proportion of small, old firms which suggests that the competitive pressure to improve and grow, or shrink and eventually exit, may not be as strong in New Zealand as it is in other OECD countries.

[38]The New Zealand data also have the advantage of being linked to several data sources (such as GST returns and pay-as-you-go employee tax records). Therefore, true firm exits and entries can be largely differentiated from continuing firms with sporadically missing production data, as demonstrated in Maré et al. (2015).

log-normal assumption.

Figure 9: Decomposition of potential TFP gains[a][b]



[a]Calculated using Equation 22.
[b]Components are the weighted mean across industries, where θ_s is used for the weights.

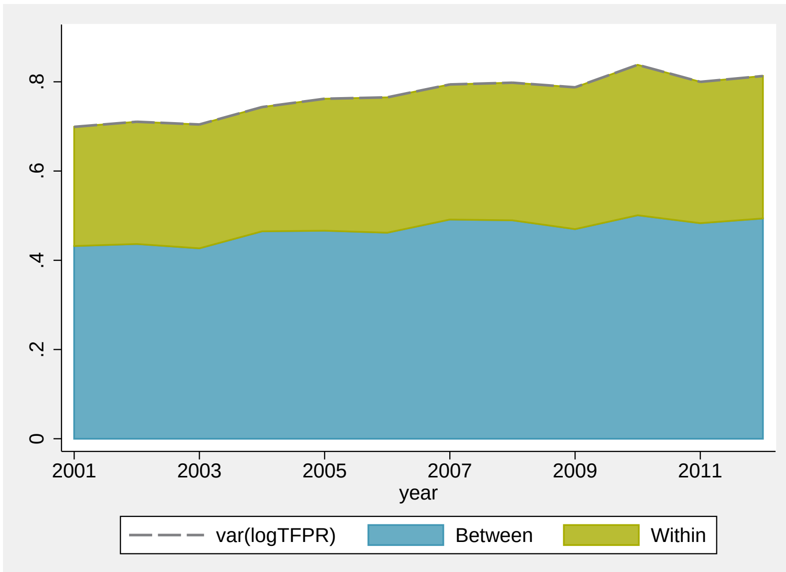
Figure 9 decomposes the HK potential TFP gains into output distortion variance, capital distortion variance and the covariance between the two distortions using Equation 22. Output distortions are higher than capital distortions, but are generally flat or even slightly decreasing over time, while capital distortions are increasing over time. This suggests that the increase in misallocation over the 2000s was mainly due to increases in capital distortions.

Covariance between the distortions is negative, which means that firms with high output distortions do not also have high capital distortions in general. This finding is different from international literature, for example, Ryzhenkov (2015) using Ukranian data and Chen and Irarrazabal (2015) using Chilean data find a positive covariance between output and capital distortions (ie, that high output distortions are usually accompanied by high capital distortions).

Decompositions by sector are not shown here, but are fairly similar to the overall pattern displayed in Figure 9. For the primary sector, the main difference is that the contribution of capital distortions is slightly higher than the contribution of output distortions. However, the primary sector still exhibits the same pattern of increasing capital distortions and steady (or even slightly decreasing) output distortion contributions. The goods-producing sector also exhibits a similar pattern to the overall trends. The only difference is that the covariance of distortions is increasing (ie, becoming less negative) in the goods-producing sector after 2008. The manufacturing sub-sector, however, does not exhibit this increase in the covariance. In services, the patterns are very similar to the overall patterns.

I also decompose the TFPR variance into between- and within-group components, where groups are quartiles of physical productivity (Figure 10). Therefore, an increase in the dispersion of TFPR over time could be due to the a divergence of TFPR in the tails of the distribution away from the median TFPR (ie, increases in the between-group component) or an increase in the variance of TFPR within productivity bins (ie, an increase in the within-group component).

Figure 10: Components of var(logTFPR)[a b]

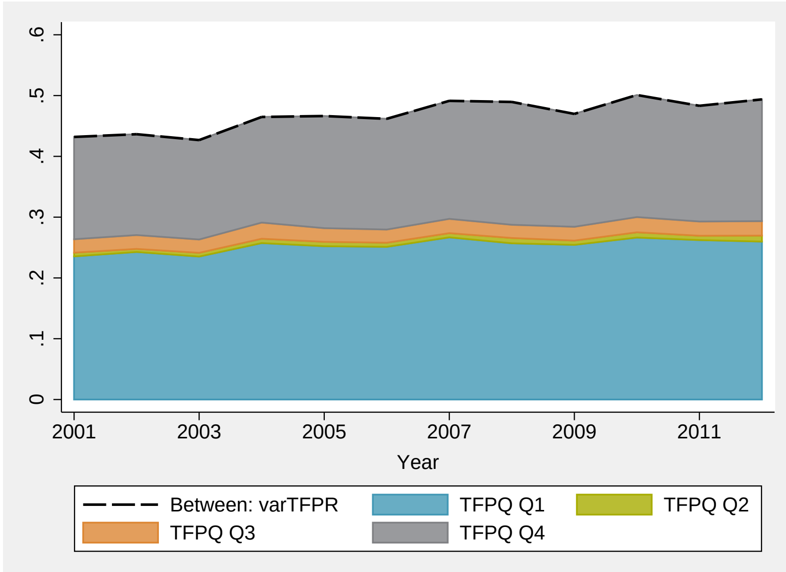


[a]Calculated using Equation 23.
[b]Components are the weighted mean across industries, where θ_s is used for the weights.

The between-group component accounts for a larger share of the variance of revenue productivity than the within-group component. Over time, both components are increasing, however, the within-group component is growing faster. This suggests that the increase in misallocation over time is due to both the TFPR tails becoming thinner and the dispersion of TFPR within groups increasing, but that the latter increase is a greater contributor to the increase in misallocation.

Figure 11 provides a further decomposition of the between-group component in order to see the key productivity groups responsible for resource reallocation. The results show that the reallocations occurred mainly in the lowest and highest productivity groups. That is, the main reason for the increase in the between-group variance is that the average TFPR of the bottom and top quartiles diverged from the mean.

Figure 11: Between component of var(logTFPR) by TFPQ quartiles[a]



[a]Calculated using Equation 23.

5 Conclusion

New Zealand's poor productivity performance over several decades has seen its incomes per capita losing ground against other OECD countries. In addition, like many countries, New Zealand's TFP growth has slowed in recent years, with this widespread slowdown preceding the onset of the Great Recession. Some international studies suggest that an increase in misallocation may be one of the culprits behind the slowdown.

To investigate the role of within-industry resource allocation in New Zealand's productivity performance in recent years, this paper applies the Hsieh and Klenow (2009) (HK) method to New Zealand firm-level data from 2001-2012. It finds that misallocation has increased over time across all examined sectors (primary, goods-producing and services). Misallocation in the services sector is higher than in the goods-producing sector, which is consistent with international studies using the HK method, as well as the broader literature on productivity in the services sector. However, misallocation has increased more in the primary and goods-producing sectors (and in particular, in the manufacturing sub-group of the goods-producing sector). Within the three sectors, it appears that the increase in misallocation has been relatively widespread, with the majority of industries experiencing an increase.

A first pass at the question of whether within- or between-industry allocation has been more important in New Zealand suggests that within-industry allocation is much more important. Further work may extend this analysis by applying Oberfeld (2013)'s method to examine the relative importance of within- and between-industry allocation in a more systematic way.

An examination of the actual versus the efficient size distribution suggests that many small firms are too large. That is, given their level of TFPR, small firms tend to overproduce relative to their efficient level. The general explanation given for this result internationally is that small firms are subsidised through vehicles such as size-contingent policies and less stringent enforcement of tax and regulations. Given the policy environment, this argument is harder to make for New Zealand. I postulate that New Zealand firms with low TFPR are able to grow larger than their optimal size due to the limited extent of the market and a lack of competition. In order to investigate this theory further, future work may look at these results by sector and industry in order to assess whether there is a relationship between industry characteristics (such as at the degree of tradability) and the size distribution.

Initial decompositions suggest that output distortions are more important than capital distortions, but that capital distortions have been increasing over time and are therefore key to the increase in misallocation over time. However, there is some doubt about the underlying assumptions required for these decompositions, so future work may investigate alternative decomposition techniques.

The next steps of this strand of research will aim to provide greater insight into the reasons behind the increase in misallocation. As well as taking a closer look at the types of distortions driving the observed increase in misallocation, future work may look at the firm- and industry-level characteristics associated with the increase in misallocation. For example, international work has highlighted the role of capital distortions, particularly among credit-constrained, young firms. This work has highlighted the importance of within-industry allocation to TFP growth, which in turn is of crucial importance to living standards. This further analysis would, therefore, provide another step towards building our understanding of this important issue.

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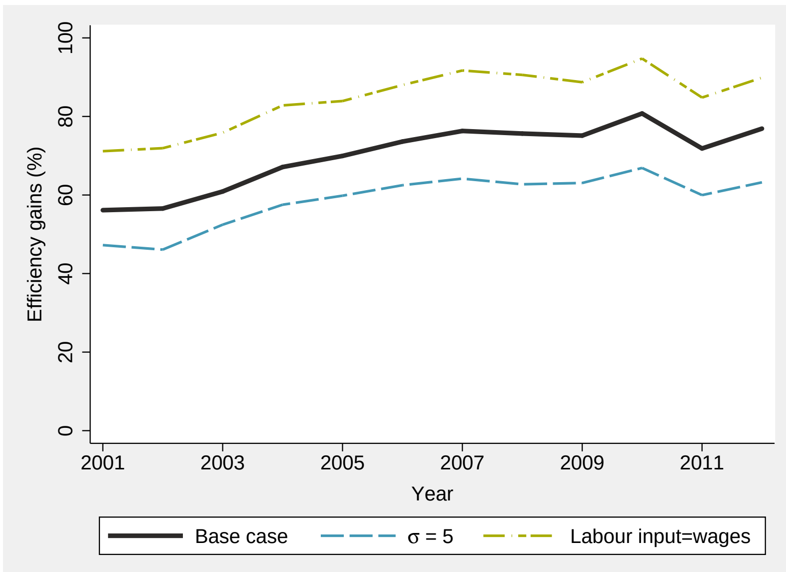
Appendix A Robustness tests

This appendix presents the results from two robustness tests. First, as discussed in Section 2, it sets the elasticity of substitution parameter, σ to 5 and compares it to the base case of $\sigma = 3$. Second, it uses the total wage bill as a measure of labour input, and sets the wage rate equal to 1, as discussed in Section 3.

Figure 12 presents these robustness tests along with the base case that is used through the main body of the paper. The use of $\sigma = 5$ instead of $\sigma = 3$ results in lower efficiency gains than the base case, while the use of the total wage bill for labour input increases the efficiency gains. The overall trends in efficiency gains over time, however, are extremely similar in all three cases. These results illustrate the point made in Section 4 that measuring changes over time is likely to be less problematic than measuring the level of misallocation.

Figure 12: Potential TFP gains: Robustness tests[a b c]



[a]The 'Base case' is the case presented in the main body of the paper. It sets $\sigma = 3$ and uses employment (ie, the sum of FTEs and working proprietors) as the labour input measure.
[b]$\sigma = 5$ sets σ equal to 5 instead of 3, but is the same as the base case in all other respects.
[c]'Labour input=wages' uses the total wage bill as the labour input measure as opposed to employment, but is the same as the base case in all other respects.

Table 3 provides the same robustness tests by sector. The results are similar as the overall results presented in Figure 12. The case where σ is set to 5 provides the lowest level of potential gains, the use of wages as labour input provides the highest level, and the base case is in the middle. Once again, while the use of a higher σ or a different labour input measure changes the level of potential gains, it does not really vary the changes over time.

Table 3: Potential TFP gains (%): Robustness tests by sector[a]

Primary	Base case	$\sigma = 5$	L=wages	**Goods-producing**	Base case	$\sigma = 5$	L=wages
2001	87.8	62.3	95.9	2001	36.2	30.0	45.2
2002	63.7	34.6	68.4	2002	39.2	31.5	48.1
2003	74.1	49.2	78.6	2003	49.1	44.8	59.7
2004	108.1	76.9	113.8	2004	55.2	52.0	66.6
2005	106.8	70.9	114.1	2005	56.1	52.6	66.9
2006	122.5	83.6	129.2	2006	59.3	54.5	69.8
2007	147.9	104.4	156.1	2007	61.0	57.0	72.2
2008	145.3	99.8	151.9	2008	59.7	55.5	72.1
2009	118.5	76.3	123.5	2009	63.4	60.3	74.7
2010	166.1	101.6	169.5	2010	69.9	66.6	83.4
2011	161.0	107.3	170.7	2011	58.0	54.8	70.1
2012	152.9	106.0	163.0	2012	66.6	63.0	79.1

Services	Base case	$\sigma = 5$	L=wages	**Manufacturing**	Base case	$\sigma = 5$	L=wages
2001	71.7	61.8	93.7	2001	21.0	12.0	25.2
2002	71.2	60.7	94.5	2002	24.5	13.5	28.7
2003	68.7	59.0	88.9	2003	36.8	29.5	42.4
2004	71.7	59.4	91.9	2004	43.6	36.4	50.0
2005	76.1	63.8	93.5	2005	44.4	37.2	51.0
2006	79.0	65.9	97.0	2006	44.5	36.0	49.7
2007	80.5	65.2	99.5	2007	45.3	37.2	50.9
2008	79.2	63.4	96.4	2008	41.0	32.7	47.0
2009	79.0	63.5	94.9	2009	47.3	40.2	53.0
2010	79.7	63.5	94.7	2010	55.6	47.9	61.8
2011	74.1	59.4	87.8	2011	41.8	34.5	47.0
2012	76.6	59.7	90.0	2012	47.9	40.2	53.4

[a] See notes to Figure 12 for details.